10. Bank Lending and Credit Risk

"A debtor is someone who owes money;
A creditor is someone who thinks they will get it back"

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10.1 Introduction

Credit risk is, hardly surprisingly, generally regarded as the major type of risk faced by banks. After all, the main business of banking is making loans – which carries the risk that the borrower will default and the bank will incur a loss. (But credit risk can arise in other ways as explained in the next section).

For the bank, then, assessing the risk associated with any potential loan is important, and obtaining information to assist in that assessment is critical. Some important information sources, and techniques of credit assessment, are discussed in later sections. The bank is also subject to a range of regulations, most notably responsible lending obligations (RLOs), in making loan decisions which are also discussed later. Monitoring customers with outstanding loans, and having loan contract terms which enable the bank to act, to reduce the risk of non-repayment and loss to the bank, is also important.

Of course, the bank needs to consider the risk of its overall loan portfolio. There will be some degree of correlation between defaults on the loans in its portfolio, with a higher correlation increasing the risk of larger loan losses occurring in some periods (even if the average level of loss over a long period is the same). This is generally considered in the context of the distinction between *expected loss* and *unexpected loss.* In any category of borrowers there is some probability that full repayment of a loan will not occur, and banks will assess the expected loss associated with that, and aim to cover it by setting of an interest rate on that category of loans which reflects the expected (or average) loss rate.

Better categorising of borrowers to get more precise and accurate estimates of expected loss for individual borrowers and setting interest rates reflecting that, is the holy grail of bank lending. More accurate pricing of loans, such that low-risk borrowers get lower interest rates, should lead to the bank attracting such borrowers and deterring higher risk borrowers. If competitor banks are less able to achieve such targeted pricing, low risk borrowers will effectively be subsidising high risk borrowers – which is arguably unfair - and will also lead to low risk borrowers migrating to other banks. Such risk-based pricing is becoming more common but has not been a feature of many types of lending (particularly at the retail level) in years past. Determining the appropriate interest rate to charge for different levels of credit risk is an important element in bank lending which is discussed later under the topic of *loan pricing.* Also important in this regard is the setting of loan loss provisions which should absorb expected losses on the loan portfolio. These provisions will be deducted in calculating the amount of equity capital which the bank has available to absorb unexpected losses.

The issue of *unexpected losses* is handled differently by the bank through modelling of the loss distribution of the loan portfolio and the calculation of adequate equity capital to absorb unexpected losses in any period. For example, if there is a 1 per cent chance that the unexpected loss in the next year on the loan portfolio is $100 million, then the bank will need equity capital (after provisions for expected losses) in excess of that amount to be 99 per cent that it will not become insolvent in the next year.

To calculate the probability distribution of unexpected losses on a loan portfolio, highly technical statistical techniques have been (and continue to be) developed by banks and consultants, some of which are briefly considered later. As well as enabling the amount of equity capital needed for the bank, the unexpected loss distribution also feeds indirectly into the pricing of different categories of loans. A category which requires a larger equity capital essentially involves a funding mix involving more equity and less deposits/debt. Bankers generally regard equity as being a more expensive form of funding, and thus the average cost of funding this category of loans is seen as higher. This gets reflected in loan pricing formula via a higher weighted average cost of funding.

Regulatory requirements

APRA produced prudential standard APS 220 (Credit Quality) in 2020 and Prudential Practice Guide APG220 in 2021 setting out what it expects of banks and ADIs in the management of credit risk. The current version of APS 220 commenced at the start of 2023. APS220 requires ADIs to have a credit risk management framework appropriate for their size and complexity which "must include a credit risk appetite statement, credit risk management strategy, credit risk policies and processes, a credit risk management function, a management information system and an independent review process." It also sets out requirements for recognition of impaired loan facilities and resulting provisioning requirements. Other than impairment and provisioning requirements, the standard and guide are not prescriptive, but more principles based setting out expectations for Board oversight and policy formulation and internal organisational arrangements needed for management of credit risk. Banks are free to choose their preferred methods and models for assessing and managing credit risk. One specific requirement, however, is that in lending to individuals, banks need to "assess an individual borrower's repayment capacity without substantial hardship". APRA requires banks to make such an assessment using a higher interest rate than currently prevailing and in October 2021 increased the buffer involved to 3 percentage points from its previous level of 2.5.

One of the new requirements introduced in the current version of APS 220 is for banks to be operationally prepared to limit growth in higher risk residential mortgage lending if required by macro-prudential policy measures. Limiting loans at high debt/income or loan/valuation ratios are examples.

10.2 Sources of Credit Risk

Making loans is a defining characteristic of banks which leads to their taking on credit (default) risk. But banks take on credit risk in other ways.

Customer Default Risk

One is via the provision of guarantees provided by the bank that customers will pay back a loan made to them by a third party. Another is a guarantee that the customer will make payment for goods to be provided to them by a third party – such as in an international trade transaction. The latter form of financing comes under the general heading of *letters of credit* and is an important feature of *trade financing* (discussed in Chapter 14).

Another source of default risk is through the granting of loan commitments, which give the customer the right to draw down funds (up to some agreed limit, at a time of the customer's choosing) in the form of a loan from the bank. These do not show up on the bank's balance sheet until drawn upon, and the unused limits are an *off-balance sheet (OBS)* exposure.

At the retail (personal) level, these were historically most common in the form of an *overdraft* facility (perhaps referred to as a *line of credit*). Nowadays individuals will generally have such access to credit via a credit card limit. This is often referred to as *revolving credit,* in the sense that the customer can draw against the limit, repay and then redraw again – whereas repayment of a standard loan terminates the availability of that credit. In recent years some banks have also taken on credit exposures by provision of Buy Now Pay Later (BNPL) facilities (discussed in Chapter 8). Also, important OBS credit exposures as (non-revolving) loan commitments at the individual level are approvals for housing loans which have yet to be drawn upon (due to the time taken for settlement, or through "pre-approval" for individuals looking for a property to purchase).

Many banks provide "redraw" facilities on mortgage loans (enabling the customer to make payments greater than those scheduled, and drawdown those excess payments if desired at some future date). For such loan accounts the credit exposure is greater than the outstanding balance, since the customer has an implicit loan commitment. Other banks offer something similar by way of an "offset account" where funds deposited in that account are credited against the loan balance in calculation of principal outstanding on which interest must be paid.

Loan commitments are particularly important for business lending – providing businesses with the flexibility to draw funds in periods of cash shortages.

Kashyap, Rajan and Stein (JF,2002) argue that loan commitments create a liquidity risk for banks, and build a model to explain why banks, who offer at-call deposits are most commonly the only types of financial institutions which provide loan commitments. Negative (or less than perfect positive) correlation between unexpected outflows of funds from deposit withdrawals and drawdown of loan commitments, reducing the variability of the bank's net cash flows, is fundamental to this result.

Banks also make investments in securities such as sovereign or corporate bonds or notes with varying degrees of default risk.

Counterparty Credit Risk

Via their transactions in financial markets, banks are also exposed to counterparty credit risk. This could arise from derivative transactions where they have a positive NPV position as a result of market movements, but there is a risk that the counterparty may default on the payment – such that the expected profit on the position does not eventuate. For this reason banks are required under IFRS 13 to make a *Credit Valuation Adjustment (CVA)* when accounting for the value of a particular position as discussed here. This would mean that the value recorded would be less than the amount assuming zero risk of default (such as given by the Black-Scholes value of an option), and reflects the "fair price" associated with exiting the position. Changes in the credit rating of a counterparty could lead to changes in the market value of a position, as occurred in the GFC, and under IFRS 13 these changes would be recognised in the P&L (income) account[1]. The Basel 3 standards impose a CVA capital charge for positions in the *trading book* of the bank.

Many derivative positions, such as swaps have a zero NPV value at initiation, but subsequent market movements may lead to the position having a positive or negative value (with the former implying the possibility of default risk and loss of expected income). Calculation of *Expected Future Exposure (EFE)* is one technique for dealing with this, and was essentially incorporated early on in a simplified fashion in the Basel capital requirements for OBS credit risk by requiring capital for potential exposure. Basel 3 involves more sophisticated approaches.

There is also provision for *Debit Valuation Adjustment (DVA)* in which the accounting value of the bank's own liabilities would be reduced by recognising that default might occur, such that the market value would be less than the "risk free" value of the position.

A particular complication is what is called *wrong-way risk*, referring to a situation in which there is a positive correlation between the size of a (mark-to-market) credit exposure to a counterparty and the default risk of that position. For example, if the underlying price moves favourably for the bank's

[1] The EBA also refers to Funding Valuation adjustments used by some banks where they have an exposure to a counterparty who does not provide collateral, but in hedging that position they would be required to post collateral.

position in a derivative, the (default-risk-free) market value of that position would increase, but this could be offset by a reduction the counterparty's ability to honour their obligation. Wrong way risk was a concern for banks which had bought credit default swaps from the insurer AIG prior to its failure in the financial crisis.

Where there is not immediate settlement of transactions (delivery versus payment) then DVP is another potential form of credit risk. This could occur in inter-bank settlements, such as the famous Herstatt Bank failure in 1974, giving rise to the term *Herstatt Risk*. Cases such as that (and technological advances) have spurred the development of *real time gross settlements* and other mechanisms to prevent risk arising from DVP lags. In international finance, the cooperative development of the *CLS Bank* *(Continuous Linked Settlement)* has been important to reduce such counterparty risks. (This BIS article gives a simple explanation of CLS Bank activities). Since the GFC, international agencies have been promoting and mandating the use of *Central Clearing Counter Parties (CCPs*) for OTC derivatives to, among other things, reduce counterparty exposures. This recent BIS article provides an overview of recent developments re CCPs and their role in risk management.

Finally, banks may also take on credit risk via provision of credit enhancements such as the writing of credit default swaps.

10.3 Credit Risk Assessment and the Lending Process

Traditional Approaches

Traditional approaches to assessing the credit risk of a potential borrower are often referred to as application of the 5C's by a loan officer. These are: Character; Capacity; Capital; Collateral; Conditions. See here for a brief description of how banks assess these factors in the case of small businesses. Judgement by the loan officer (and higher levels within the bank if the loan is of a size greater than the officer's delegations) would then see the loan be given an internal credit rating score. Depending on that appraisal, the loan would be rejected or approved (perhaps for an amount less than applied for) and an interest rate determined for the loan. While, in principle, interest rates charged could be linked closely to the credit score, such risk based pricing was not always common for certain categories of loans – particularly at the retail level – until recent decades. Peer to Peer (or Marketplace) lending platforms generally involve explicit risk-related pricing for retail borrowers, with this being one point of difference to standard bank retail lending.

The loan officer will need to obtain a wide range of information from, and about, the borrower and the purpose of the loan, either directly from the borrower or by accessing other information sources. Table 1 provides an example of the types of information required for a commercial loan and the approach which should be taken by the loans officer in developing a position on the acceptability of the loan application. Obviously for a personal loan or a residential mortgage loans a somewhat different checklist would apply, but still aimed at getting sufficient information to come to a view on the 5C's listed above. The loan officer would also investigate whether third party guarantees of repayment (eg parents in the case of a housing loan, or directors in the case of a loan to a company) might be available.

TABLE 1: LOAN ASSESSMENT BASICS

What is the deal, do we really understand it, (whether new deal, increase or review)? Is it logical, transparent and does it make commercial common sense? Do we need more information before going any further?
Do we know who the parties to the deal are - the wider group and their involvement. Do we understand their history, achievements, reliability or otherwise?
Does the initial structure and servicing programme suggested meet the bank's basic guidelines?
Do we have all the required information on which the deal is to be based? Cash Flows, Financial Statements, SPs, business plans, development proposals, tenancy schedules, quotes, plans, statutory approvals, aged debtor/creditor listings and industry intelligence.
How do we interpret the forecast cash flows, what yardsticks are we using to ensure relevance and reliability?
Financials, Trading P&L and Balance sheet. Do we understand what they are saying and what they are not saying? What are the implications of evident or emerging trends? What questions should we ask?
Have we conducted interviews at the business site; what is our reaction to the physical assets and the apparent skills, experience, working ability, character and cooperation of the principals and their key staff? Are we happy with the negotiation process?
Have we assembled and analysed all the data with which to prepare our submission? Does it all consistently and reasonably match the customer's original proposal and point in the desired direction or are there gaps we need to investigate and resolve first?
If the application should be declined, then do so. High loan pricing is not a mitigation for a specific credit risk.
Do we need valuation advice to support the deal; at what point do we ask for formal valuations?
Source: Damien Morris (personal communication)

Once information has been gathered then a case would need to be put together to underpin a decision, or recommendation to the committee or executive with authority, to approve such a loan. While an individual loan officer will generally have authority to approve loans up to some specified size, approvals for larger and more complex loans will require sign-off by more senior staff or designated committees. Table 2 provides an example of a checklist for making a submission to such a higher authority.

Table 2: Loan Recommendation Submission Checklist

Have we formulated persuasive quantitative and qualitative arguments for the submission?
Do we have them in a logical order that will flow and build a compelling case such that the power and clarity is evident to Credit Sanctioning on first reading?
Is the expression complete yet succinct so that we present what is relevant but do not drown the reader in superfluous or self-evident data?
If valuations are involved have we read and interpreted them correctly, weighing both upside and downside variables?
Do we understand the monitoring requirements for the proposed exposure? Are they achievable – for the bank and the borrower? It is pointless to seek approval based on monitoring requirements that are so arduous that default quickly occurs.
Finally, have we clearly demonstrated that we understand all elements of the proposal, its risks and appropriate returns and mitigations which all fit within the Bank's framework and policies for lending. Does the applicant understand and agree?
Source: Damien Morris (personal communication)

Statistical Models for Credit Assessment

For many years, lending institutions have augmented or replaced subjective judgments of loan officers about the default risk of a loan with statistical modelling. Inherent in these approaches is the assumption that the relationship between default probability and borrower and loan characteristics can be estimated from available data on past loans, and used to forecast the default probability of a new loan applicant.

The simplest approach would be along the following lines. From the database of past loan outcomes identify for each loan whether it defaulted or not, and collect relevant information about the borrower/loan characteristics, such as borrower income (denote that as I), wealth (W), loan size (L), security (collateral) value (V). Denoting loan outcome as y = 1 if the loan defaults and y = 0 if the loan does not default, a linear regression of y on the characteristic variables (and an error term (u) of the form:

$y_i = \beta_0 + \beta_1 I_i + \beta_2 W_i + \beta_{3L} L_i + \beta_4 V_i + u_i$ $\qquad$ i = 1……N where N is the number of observations

can generate estimates of the β values (the sensitivity of default probability to a unit change in the associated characteristic). Using those estimates and the characteristics of the loan applicant, an idea of their probability of default can be derived – with higher predicted y values indicating a greater probability of default.

The linear regression used above is simplistic in the extreme and provided simply to illustrate the type of approach which can be used. One fundamental problem with it is that predicted values derived from it could be below zero or above one, whereas an ideal outcome would be where predicted values lie within the feasible range of 0 to 1 and can be interpreted as the probability of default. Another is that much more suitable explanatory variables could be used such as repayment/ income or loan/valuation ratios. A third problem is that the coefficient estimates will reflect the loan approval processes involved in the past. The data base of past loans will not include loan approvals which were rejected but may have been good risks! A further problem is that of classifying loan outcomes solely as default or non-default, since some loans may eventually be repaid, but late and involving significant cost of intervention to the lender. Moreover, in many cases the database might have only a very small number of defaults relative to non-defaults, reducing the confidence one can place in the estimated coefficients.

Logit and Probit models

A common method to overcome the problem of linear regression models generating predicted probabilities of default of below zero or above one has been to use either Logit or Probit models. These involve transforming the relationship between the outcome variable and the characteristic (explanatory) variables in a non-linear way. Not only do these models ensure that the predicted default probabilities are between zero and one, but they also imply that changes in the value of a characteristic have different effects of default probability dependent on the value from which the change is made. For example, a change in income could be expected to have very little effect on default probability when income is very low (and default probability high), or when income is very high (and default probability low), but have quite significant effects for mid-range income levels.

Logit and Probit models are easy to estimate with modern econometric packages, and have been for many years. But note that these only relate to default probability and not to the size of the loss – which could be the entire outstanding balance or some small proportion of that due to the value of collateral provided or other repayments received from the defaulting borrower.

Machine Learning and Artificial Intelligence

One of the potential drawbacks of logit/probit and other regression type approaches is that they required the user to pre-specify the nature of the functional form to be used. If the actual relationship between the characteristics and default probability is not of the form specified then the results will be biased. This also applies to the choice of characteristic (explanatory) variables and the particular form specified for them.

Modern computing power has made available a number of other approaches, in which the computer is “trained” to search over a database and come up with the “best” relationship between variables in the database – where that relationship could be quite complex. The “best” relationship will be derived by testing the performance of alternative relationships both within the data being used, and also on a “test” data set within the database but excluded from the searching process. “Best” is specified by the operator, and could be in the form of minimising some form of prediction error. As new data is added to the database, the machine "learns" and adapts the relationship to best incorporate that new data. This Moody's 2017 article provides some discussion and analysis of alternative types of machine learning approaches.

As more "big data" becomes available, such techniques reliant on machine learning and artificial intelligence are becoming more widespread, including in the case of credit assessment. While improvements in default prediction can arise from such processes, there are a number of concerning aspects. One is the issue of who is ultimately responsible for loan approvals when an algorithmic process is being used. If (when!) errors occur and a large loan fails badly, or an inappropriate loan is made to a customer, which bank executive is held to account. Moreover, who will be able to delve into the millions of lines of code involved in the algorithm to identify the cause of failure and ensure it won't happen again!

A second problem is the way in which inappropriate biases might be incorporated into such algorithms and thus into credit scoring and loan approvals. Fuster et al (JoF, 2022) for example investigate the effects of machine learning on credit markets and argue that the technology may be able to identify, and incorporate into the algorithm, borrower characteristics (such as race, ethnicity, gender) that turn out to be relevant to default rates, but which are not permitted to be used in loan assessment. (They refer to this process as "triangulation of otherwise excluded characteristics").

Fin Tech and Lending

Some examples of fintech lenders are BNPL operators, peer to peer (or marketplace) lending platforms, and supply chain financiers (which are discussed in Chapters 2 and 8). But fintech also incorporates technology companies providing services to traditional banks, as well as banks developing technological process in-house.

Berg et al (ARFE 2022) provide a recent survey of the implications of the growth of financial technology (FinTech) for lending practices and loan markets. They note that there are two main effects. One is on the nature of borrower-lender interactions, with new processes enabling more efficient, less costly, and faster loan decision making, such as via on-line application processes. (The downside is that financially naïve individuals may be enticed by greater ease of application processes to apply for credit which is unsuitable for them). The second is increased ability of lenders to incorporate more information into their loan decision-making processes to make quicker and better credit decisions and improved subsequent monitoring of borrowers. (Quicker decision times can, in conjunction with ease of application also run the risk of enticing applications for credit which may be unsuitable for the applicant. This has been one criticism made of BNPL).

Berg et al note that fintech firms have generally been subject to weaker regulation than traditional bank lenders, and that this may be one factor in the relatively rapid recent growth of such credit. This weaker regulation reflects partly the novelty of some of the credit products meaning that they have not be captured by extant regulation, as well as their use of non-deposit funding meaning that they are not subject to bank regulation. But the use of new technology and systems enabling more efficient processes is also relevant. Whether fintech firms have demonstrated advantages in credit assessment over traditional banks (which also use fintech advances) is yet to be shown.

Looking ahead, increased regulation of fintech is to be expected because of concerns about financial consumer protection and, as the sector grows, issues related to financial stability.

10.4 Credit Bureaus and Open Banking

Access to information about the borrower is clearly an important ingredient into loan quality assessment. As well as information supplied directly by the borrower (such as lists of assets, income statements, tax returns) or available to the bank from past dealings with the customer (transactions account behaviour, any past repayment experience etc) lenders will look to external sources of information.

An important source of information at the retail level is information available from *Credit Bureaus* who obtain information from banks (and utilities) about individual's credit histories and provide that in response to queries from potential lenders. A common development has been for credit bureaus to apply statistical techniques to the data they collect to generate a *credit score* such as the *FICO* score in the USA. The main credit bureau in Australia is the US multinational Equifax which acquired *Veda* (previously known as *Baycorp Advantage*), in February 2016. Others include Experian and Illion (which is associated with consumer finance marketplace Credit Simple). The major banks provide credit data to Equifax, Experian and Illion.

Dunn and Bradstreet provides a similar type of service internationally by providing credit quality information about businesses. Its Australian operations were spun off in 2015 and rebranded by the acquirer as Illion. Another provider of credit data on smaller businesses is Equifax. Also operating in this area is CreditorWatch. At the larger corporate and institutional (and government) level, there is information available from the credit rating agencies (S&P, Moody's, Fitch) who provide credit ratings (letter grades) for those entities (and their specific debt securities) which have requested and paid for such ratings.

Comprehensive Credit Reporting

Credit Bureaus can receive two types of data from their participating financial institutions. "White" data is positive information about credit-related activities of individuals, while "black" data is negative information. The latter category includes information about loan defaults or poor repayment history. It also includes numbers of loan applications, reflecting the view that more applications may be indicative of a stressed financial position. The white data includes such things as account information, credit limits, type of credit used, and loan repayment information. Finder provides a list of what is included.

Historically, Australian credit bureaus only received black data from banks and other participants, even though including white data would improve the information available for assessing loan applicants. One explanation for this can be found in the dominance of the major banks each with large market share and unwillingness or inability to collaborate. If any one bank were to provide white data on its customers, that would only benefit its competitors and potentially lead to a loss of market share. If all banks did so, however, competitive ability losses from sharing information would be offset by gains from access to greater information. The socially optimal outcome of greater information availability from "comprehensive credit reporting" (involving both black and white information) for loan assessment was thwarted by private incentives.

This was recognised by the AFSI (Murray Inquiry) and reflected in its November 204 Final Report in its Recommendation 20:

"Support industry efforts to expand credit data sharing under the new voluntary comprehensive credit reporting regime. If, over time, participation is inadequate, Government should consider legislating mandatory participation."

On 2 November 2017, the Treasurer announced that the government would legislate for mandatory comprehensive credit reporting to come into effect by 1 July 2018.

This followed an earlier Budget announcement that if a 40 per cent reporting threshold was not reached by end 2017, such mandating would occur. But actual implementation was much delayed (privacy issues for borrowers in hardship circumstances, being one cause, together with the Covid crisis and amendments required by the Senate) and the legislation not passed until early 2021. Large ADIs were required to meet a 50 per cent reporting requirement by July 2021 and 100 per cent a year later. Those institutions not mandated to report will be able to access the expanded information available if they too elect to provide comprehensive reporting.

Credit Bureaus use the data they receive to calculate "credit scores" for individuals and provide these to participating institutions as a summary measure of the data they have received. A poor credit score can obviously lead to an individual being rejected for loans, so that it is important that the underlying data is correct and the modelling used has strong foundations. On feature of the legislation is that individuals are able to obtain information on their credit score free of charge (see here for example), enabling them to check its veracity and identify ways in which they may be able to improve their score.

Open Banking

A major government initiative in recent years has been the introduction of Open Banking as an initial part of the Consumer Data Right, following a review conducted by Scott Farrell. Operating since July 1, 2020, Open Banking gives customers the ability to share their banking data with third parties which have been accredited by the ACCC. Those third parties could be other banks or specialist technology/advisory firms. Either way, information about the individual's banking history (loans, transactions etc) can then be made available to alternative providers of financial services - reducing the costs associated with applying for loans from alternative providers. The specialist firms can also develop financial tools and models which, by drawing on the individual's data, can assist the individual in managing their finances and identifying suitable products for them.

The roll out of open data has involved an increasing range of data items and extension beyond the major banks to whom it was first limited. Accredited third parties can obtain the data of customers who have permissioned them either by "screen scraping" data from a customer's internet banking app (although that can raise password security concerns) or by using APIs (Application Programming Interfaces) developed by the bank.

It is too early to assess the effects of the introduction of Open Banking on lending. In principle it should reduce the inherent information advantage of the customer's current bank over competitors, since the latter will now be able to access the information which was once privy only to the customer's current bank. Open Banking (and its extension to other parts of the financial system) is of key interest to the "fintech" sector, who perceive opportunities for product and services development based on application of modern computer, communications, and data analysis capability. The submissions to a recent Treasury consultation give an idea of the level of interest and some of the complex issues involved.

Draft legislation announced in late 2022 involves an "action initiation" power whereby the CDR would also involve customers giving third parties the ability to conduct payments and transfer that customer's account to another institution if deemed desirable. "Screen scraping" as a way of obtaining data is also likely to be outlawed at some point in the near future.

10.5 Bank Credit Assessment Methods and Loan Management

Most banks will have their own internal credit rating ladders for different groups of borrowers, and the approaches they use to allocate ratings to customers will differ depending upon the customer segment. Different information and credit assessment techniques will be used for retail, SME, corporate, government counterparties, and potentially within those groups depending upon the type of loan products being considered (such as credit card applications versus unsecured personal loans or home mortgages). And clearly the size of the loan involved will influence how many resources will be invested in the loan assessment process and the extent to which risks of misclassification of borrowers will be tolerated. For example, at the retail level where there are very large numbers of customers, a cost-benefit calculation might lead to reliance on some automated credit scoring model to reduce human resource costs in the appraisal process. Most banks will use various statistical models of credit risk assessment (discussed later).

Figure 1 illustrates the relative reliance on statistical models, expert judgement and external ratings for different categories of borrowers used by ANZ. Where there are large numbers of relatively homogenous borrowers (the retail portfolios) statistical models are generally used, although lending staff are required to review model outcomes in the context of the knowledge they have. Scores from the statistical models are calibrated to PDs. Modelling is also done for EAD and LGD.

IRB Asset Class	Borrower type	Rating Approach
Corporate	Corporations, partnerships or proprietorships that do not fit into any other asset class	Mainly statistical models Some use of expert models and policy processes
Sovereign	Central governments Central banks Certain multilateral development banks Australian state governments	External rating and expert judgement
Bank	Banks In Australia only, other ADIs incorporated in Australia	Statistically-based models Review of all relevant and material information including external ratings
Residential Mortgages	Exposures secured by residential property	Statistical models
Qualifying Revolving Retail	Consumer credit cards <$100,000 limit	Statistical models
Other Retail	Small business lending Other lending to consumers	Statistical models
Specialised Lending	Income Producing Real Estate Project finance Object finance	Expert models/Supervisory Slotting[31]

FIGURE 1 ANZ CREDIT RATING APPROACHES (SOURCE ANZ 2019-SEPTEMBER PILLAR 3 DISCLOSURE)

Mortgage Brokers and Credit Assessment

One significant development in recent decades in Australia has been the growth of "mortgage brokers" who intermediate between potential mortgage borrowers and bank (or other) lenders.[2] (Generally they will be linked to an "aggregator" who provides a software platform and other services enabling them to interface their activities with those of lenders on that platform). Their activities enable lenders to expose their offerings to a larger customer base than available via branch networks or websites etc., provide borrowers with greater choice among lenders, provide information and advice to customers, and undertake some part of the credit assessment and application process. In some cases, large brokers will provide "white labelled" mortgages which are marketed as being mortgages of the broker but which ultimately are a loan contract with a particular lender. Generally mortgage brokers have received remuneration from lenders in the order of 50 basis points upfront commission and 15 basis points trail commission p.a. (based on outstanding loan balance). A government review of mortgage broker remuneration arrangements occurred in 2017, but this was overtaken by the Royal Commission's recommendation to require customers (rather than lenders) to pay for the services of mortgage brokers – which after a major lobbying effort by the industry was rejected by the Government. Instead the Government passed legislation introducing a specific best interests duty for brokers requiring them to prioritise consumers' interests when providing credit assistance.

The Royal Commission also focused on best interest duties of mortgage brokers and ASIC released Regulatory Guide RG273 in June 2020 on the implications of the resulting legislation for brokers.

Mortgage Brokers are one of a number of potential "channels" through which lenders can access potential borrowers, in addition to their own branches, internet portals and representatives. In addition banks may make arrangements with third parties (such as "fintech" companies) to "white label" mortgages. Bendigo-Adelaide bank entered such an agreement with Tic:Toc in 2017, whereby the bank designates an amount of loan funding which Tic:Toc can offer to customers and sets the variable interest rate which can be offered to new borrowers. Tic:Toc advertises that proprietary technology underlying its on-line portal enables faster processing of loans and lower commission costs for the bank, than is the case with mortgage brokers.

Loan Monitoring

Having made a loan, the bank will want to monitor the borrower to assess changes in their ability to repay, and take actions to mitigate potential losses on the loan. (Indeed, the role of a bank as a "delegated monitor" of borrowers (on behalf of multiple small lenders – the depositors), is often cited

[2] This 2018 Deloitte Access Economics report provides detail on the mortgage broking industry.

in the academic literature (following Diamond (RES, 1984) as one explanation for the existence of banks).

The most obvious form of monitoring is via ensuring that the bank systems flag any instances of a borrower not meeting scheduled repayments on time. An overdue repayment can be expected to lead to follow-up actions (perhaps not immediately, but after some policy-determined number of "days past due". (Irregular cash flow streams of a borrower may sometimes make them unable to meet the occasional repayment exactly on schedule, without meaning that there has been an increase in risk of ultimate default). These actions may be system-generated reminder notices or personal contact by the lending officer and become increasingly forceful (in terms of the actions the bank might take) as the time past due and amount outstanding increase. In general, internal loan portfolio management reports will show numbers of loans with repayments overdue by (for example) 30,60 and 90 days, with 90 days being a typical trigger for reporting a loan in default.

One simple way in which monitoring (prior to a non-repayment event) can occur is via observation and analysis of the cash flows through the borrower's transaction account with the bank. Irregular patterns or lower than usual account balances may signal developments in the activities of the borrower which are informative about the credit risk associated with the loan.

Lenders may also obtain information about an existing borrower from a range of sources. Equifax provides information on how credit managers approaches have changed over the decade to 2021 (based on its annual surveys). Technological developments enabling greater and faster collection and analysis of larger amounts of data have been an important change. Obtaining credit reports and credit scores on existing borrowers from credit bureaus such as Equifax is one way of accessing information external to the bank.

Loan Management

Once a problem with an existing loan has been identified there are a number of steps a bank can take.

At one extreme there is "forbearance" – doing nothing and hoping that the borrower's fortunes will improve such that repayment will ultimately occur. That would be rare, and even where the bank accepts that repayments may be delayed a penalty rate of interest will generally be applied to the outstanding amount of the loan.

At the other extreme, the bank could immediately "foreclose" on a defaulting borrower (where the loan is 90 days past due, for example) and, in the case of a business borrower, appoint a receiver to sell the borrower's assets to recoup amounts owed to the bank. (The legal arrangements depend on the type of borrower (individual, small or large business etc) and the type of loan contract (personal, mortgage, corporate loan etc)).

In general, neither of these extreme responses is likely to optimise the outcome for the bank (nor the borrower). The bank could instead work with the borrower to arrange an alternative repayment schedule, such as lengthening the term over which the loan is to be repaid or changing the frequency of repayments. Increased collateral could be sought from the borrower. A loan could be restructured such as providing a temporary repayment deferral period – as occurred in 2020 when banks offered wide scale mortgage repayment deferrals to borrowers who faced the risk of income losses during the Covid related economic lockdowns. (Interest continued to accrue on deferred loans). The bank could agree to accept a payment from the borrower of less than that owed in order to close the loan and avoid the costs which would be incurred with pursuing (and not necessarily achieving) possible repayment of the full amount.

A bank may even provide further loans to a borrower at risk of default, such as a "work-out" loan, if that would improve the outcome for the bank. For example, if the defaulting borrower is forced into liquidation, a fire sale of the business or its assets may not generate much for the bank. However, providing a further loan may enable the business to trade through current difficulties and ultimately repay both the original and the new "work-out" loan.

Carpinelli et al (Bank of Italy 2016) provide results of a survey of Italian bank approaches to dealing with non-performing loans which was prompted by a large growth in such loans after the GFC. They note the use of both legal processes (such as bankruptcy or restructuring) and creditor agreements (such as the bank agreeing that repayment of an amount less than that owed would be accepted as closing out the loan). They find that management of non performing loans involved costs equal to around 2.8 per cent of total bank operating costs in 2014, and that the time frame involved in recoveries or restructuring varied but was often in the region of 3-4 years.

10.6 Responsible Lending Obligations (RLOs)

Under Australian legislation (the National Credit Code) entities engaged in lending (or related advice) will need to hold a Credit Licence and possibly an Australian Financial Services Licence (AFSL).[3] The NCC imposes upon lenders, through responsible lending provisions, a requirement to ensure the suitability of the credit product offered to a retail customer (in contrast to the borrower being responsible for determining the suitability for themselves).

An illustration of Housing Lending Practices of one major Australian Bank (NAB), which indicates the role of responsible lending requirements (and prudent lending) is shown in Figure 1 (sourced from the

[3] Australian legislation does not treat credit as a financial product.

bank's April 2020 Investor Briefing). APRA's perspective on prudential mortgage lending and its supervisory approach is explained in this 2016 speech.

KEY ORIGINATION REQUIREMENTS

Income	Income verified using a variety of documents including payslips and/or checks on salary credits into customers' accounts Apply a minimum 20% shading on less certain income, for example rental income shading since 2015
Household expenses	Use the greater of: • Customers' declared living expenses, enhanced in 2016 to break down into granular sub categories; or • Household Expenditure Measure (HEM) benchmark. HEM has been in use since 2012 and enhanced in 2015 to scale for customer income and further refined in Dec-18. HEM add-ons introduced for specific customer declared expenses in Aug-19 (e.g. private school fees). Latest HEM annual update occurred in Dec-19
Serviceability	Assess customers' ability to repay based on the higher of the customer rate plus serviceability buffer (2.5%) or the floor rate (5.5%), updated in Aug-19
Existing debt	• Verify using declared loan statements and assess on the higher of the customer rate plus serviceability buffer (2.5%) or the floor rate (5.5%) • In Dec-18 tightened assessment of customer credit cards assuming repayments of 3.8% per month of the limit • In Aug-19 tightened assessment of customer overdrafts assuming repayments of 3.8% per month of the limit
Interest only	• Assess Interest Only loans on the full remaining Principal and Interest term • Maximum Interest Only term for Owner Occupier borrowers of 5 years

LOAN-TO-VALUE RATIO (LVR) LIMITS

Principal & Interest – Owner Occupier	95%
Principal & Interest – Investor	90%
Interest Only	80%
'At risk' postcodes	80%
'High risk' postcodes (e.g. mining towns)	70%

OTHER REQUIREMENTS

- In 2017 introduced Loan-to-Income decline threshold, reduced from 8x to 7x in Feb-18
- In Apr-19 introduced a Debt-to-Income decline threshold of 9x
- Lenders' mortgage insurance (LMI) applicable for majority of lending >80% LVR
- LMI for inner city investment housing >70% LVR
- Apartment size to be 50 square metres or greater (including balconies and car park)
- NAB Broker applications assessed centrally – verification and credit decisioning

66

Figure 2: Household Lending Practices at NAB (Source: NAB)

The Responsible Lending Obligations were introduced in 2010, and require essentially that the lender is able to demonstrate that it has assessed the ability of a retail borrower to meet repayment obligations out of their income, without relying on liquidation of any collateral (eg a residence). Those obligations also should be assessed at a higher interest rate than currently applies, and the ability to repay should take into account other expenditure commitments of the borrower. The requirements do not apply to SME lending even if secured against the borrower's home. ASIC provides guidance in RG209.

Assessing ability to repay is not uncontroversial. ASIC took Westpac to court in 2019 regarding its reliance on the HEM (Household Expenditure Measure) produced by the Melbourne Institute, arguing that this did not meet the requirements by failing to take into account the borrower's actual expenditure. This led to the "Wagyu and Shiraz" judgement, rejecting ASIC's arguments, with the judge noting that if a borrower was having difficulty meeting repayments given their current lifestyle, they could always cut back on consumption of fine wine and meat. In July 2020, ASIC announced that it was not going to appeal that judgement.

In 2021, the Federal Government introduced legislation to remove the RLO requirement except in the case of small amount credit contracts and consumer leases. There was much opposition to this from consumer advocates, and the legislation had not did not proceed with the change in government in 2022.

Loan Defaults and Debt Collection

If a borrower cannot meet repayment obligations, banks will typically examine alternative ways of facilitating ability to repay and/or recovering funds owing. They also will have loan contract terms which aim to avoid moral hazard by imposing penalties for late payments.

One option to assist borrowers is to extend the term of the loan, spreading principal repayments over a longer period and thus reducing the periodic repayment amounts. However, particularly for relatively new mortgages, most of the repayments are interest, such that reducing the principal component may have relatively limited effect. Allowing loan repayment holidays is another option, and this has been a major response of Australian banks to the Covid19 crisis. Interest still accrues on the loan, such that the principal outstanding increases until repayments are resumed. If repayments resume at the same rate, the term of the loan is thus extended.

Once the bank or other lender has decided that recovery of amounts owing (after seizing loan collateral – via appointment of *receivers* in the case of business borrowers) is not going to happen via negotiation with the borrower, they may appoint debt collectors. Debt collectors can put individuals into compulsory bankruptcy (details and data at AFSA) if the amount owing is $5K or more, although that threshold was been increased temporarily to $20K for 6 months from March 2020 due to the Covid19 crisis, and is currently $10,000.[4] Major debt-collection agencies are ASX-listed companies Credit Corp, Collection House, and Pioneer Credit. Others include Baycorp, CCC Financial Solutions and Panthera Finance.

The Australian Banking Association provides guidelines for debt collection arrangements for banks.

10.7 Bank Credit Risk Management Organisation

While loan approvals will be delegated within a bank to the relevant level (depending on size, complexity, customer relationships etc) banks need to have in place management systems which ensure that overall credit risk is managed appropriately. Table 3 provides an overview of one bank's approach, and Figure 3 provides an outline of the management structure for oversight and control of credit risk at that bank.

[4] There has been ongoing pressure to increase the threshold

TABLE 3: CBA CREDIT RISK MANAGEMENT

Description	Governing Policies and Key Management Committees	Key Controls and Risk Mitigation Strategies
Credit Risk (Section 8)		
Credit risk is the potential for loss arising from the failure of a counterparty to meet their contractual obligations to the Group. The Group is primarily exposed to credit risk through: ▪ Residential mortgage lending; ▪ Unsecured retail lending; ▪ Commercial lending; and ▪ Large corporate (institutional) lending and markets exposures.	**Governing Policies:** ▪ Group Credit Risk Policies, Principles, Framework and Governance ▪ Group and BU Credit Risk Policies **Key Management Committee:** ▪ Financial Risk Committee ▪ BU/SU Financial Risk Committees	▪ Defined credit risk indicators set in the Group RAS; ▪ Transacting with counterparties that demonstrate the ability and willingness to service their obligations through performance of due diligence and thorough credit quality assessments; ▪ Applications assessed by credit decisioning models, with more complex or higher risk applications referred to credit authority holders; ▪ Taking collateral where appropriate; ▪ Pricing appropriately for risk; ▪ Credit concentration frameworks that set exposure limits to counterparties, groups of related counterparties, industry sectors and countries; ▪ Regular monitoring of credit quality, concentrations, arrears, policy exceptions and policy breaches; ▪ Working with impaired counterparties, or those in danger of becoming so, to help them rehabilitate their financial positions; and ▪ Stress testing, either at a counterparty or portfolio level.

Source [*CBA 2020*]

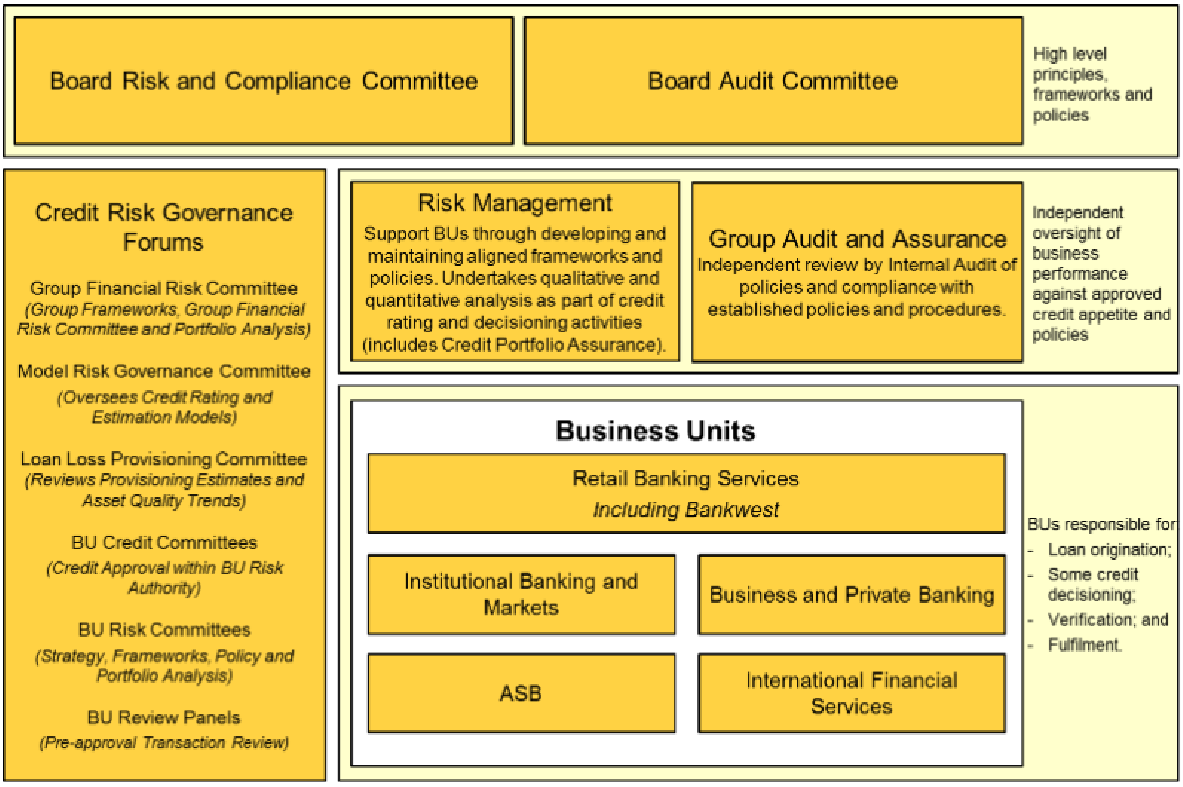

FIGURE 3: CBA CREDIT RISK MANAGEMENT FRAMEWORK

Source: [*CBA*] *2020*

10.8 Loan Pricing and Loan Terms

The pricing of loans (interest rate charged) should reflect the risk of loss from default by the borrower, while the design of loan terms (maturity, repayment schedules, collateral (security) provided, third party guarantees etc) can be structured to attempt to reduce such risk of loss.

As discussed by Edelberg (JME, 2006) in practice, risk based pricing was not particularly common amongst banks prior to the 21st century, particularly in dealing with retail clients. A recent study of the impact of risk-based pricing on lending in a particular market (auto finance in the USA) is provided by Einav et al. They find that use of automated credit scoring appeared to increase profits by about $1,000 per loan, partly via screening of higher risk borrowers and partly by price differentiation between high and low risk borrowers.

The importance of risk based pricing can be seen by supposing there are two types of potential borrowers, high risk (H) and low risk (R) and that lender A is unable to distinguish between them but lender B can do so and charges different interest rates reflecting risk. It can be expected that high risk borrowers will be attracted to lender A, while low risk borrowers will be attracted to lender B. Lender A will experience higher default rates and need to increase the interest rate charged – further deterring good borrowers.

Banks who adopt some form of risk-based loan pricing will determine a contractual interest rate such that, allowing for expected loss associated with that type of loan, the expected return will be sufficient to cover the cost of funding, operating costs, and any required risk premium.

Expected loss obviously depends on the type of loan, collateral provided, the specific borrower characteristics etc. Figure 4 below (from the NAB March 2020 Investor Briefing) gives an idea of the average historical loss rates on major loan types.

ESTIMATING LONG RUN LOAN LOSS RATE	
NAB Australian geography net write off rates as a % of GLAs 1985 - 2019[2]	**Long run average**
Home lending[3]	0.03%
Personal lending[3]	1.51%
Commercial[3]	0.54%
Australian average (1985-2019)	0.34%
Group average[4] based on 2020 business mix	**0.26%**
Group average[4] based on 2020 business mix excluding 1991-1993 and 2008-2010	**0.19%**

FIGURE 4: AVERAGE LOAN LOSS RATES

Deriving a risk-based loan interest rate

At the simplest level, consider a one year loan, with principal and interest to be repaid as a lump sum at the end of the year. The contractual repayment will be L(1+r) where L is the loan size and r is the quoted interest rate. However, the borrower might default and the lender only be able to recoup some part (or none) of the outstanding amount. The *Expected Loss* (EL) on the loan can be written as:

EL = PD x LGD x EAD

where PD is probability of default, LGD is loss given default and EAD is exposure at default.

For example, consider a $100 one year loan (L =100), with quoted rate r = 8%, PD = 0.1, EAD = L(1+r) = $108, and LGD = $40 (such that the recovery = $68 = $(108-40)).[5] Then, the expected gross return in one year is $104 = ($108x0.9 + $68x0.1), and the EL= $4. The expected rate of return on the loan is 4%.

[5] The LGD would usually be expressed as a percentage of the EAD (ie 40/108 in this example).

The bank would need to determine whether this expected return is adequate given its cost of funding, operating costs, and risk. Such an approach finds expression in the Risk Adjusted Return on Capital (RAROC) approach to performance assessment.

But the prior question is to determine how to price a loan – what interest rate to charge. To address this, think of it in terms of the usual project evaluation (capital budgeting) framework. But in this case, rather than being given a set of expected cash flows to value – what is required is to find a quoted interest rate and resulting expected cash flows which make the loan have NPV=0. This could be done using the formula below for simple loan structures. Equivalently, for more complicated, multi-period loans, one could model the cash flows expected from setting a particular contractual interest rate (and other loan terms) and ask whether the NPV calculated at the assumed WACC (cost of funds) is positive or not. The breakeven loan rate could then be determined via an iteration process.

The risk-based pricing formula can be expressed simplistically for a one-period loan as:

$r^* = OC + EL + WACC$

where OC is operating costs per $1 of loan, EL is expected loss on the $1 loan, and WACC is the weighted average cost of capital, and r* is the required loan interest rate quoted. To derive this note that the expected net cash flows (including principal repayment) are 1+r*-OC-EL, and for the $1 loan to have zero NPV, r* needs to be chosen such that the discounted expected net cash inflows equal the initial cash outflow of the $1 loan:

$(1+r^*-OC-EL)/(1+WACC) = 1.$

Some simple algebra gives the equation above.

Obviously, the practice is more complicated than this. First, the cash flows considered were before company tax. In that case where interest expense is tax deductible, the WACC becomes

$WACC = wr_e/(1-t) + (1-w)r_d$

where r_e and r_d are equity and deposit (debt) costs, w and (1-w) their respective weights in bank funding, and t is the corporate tax rate.[6] And because deposits also involve significant operating costs for banks, those costs need to either be incorporated in OC or added to deposit interest costs. Ideally, the bank will have an Activity Based Costing (ABC) system such that it can identify which operating costs are related to the loan and which are related to deposits etc. (This will be one reason why interest

6 The traditional capital budgeting approach discounts "unlevered" after tax expected cash flows (1+ c(1-t)), where 1 is return of capital and c is taxable earnings to give: NPV = [1+c(1-t)]/[1+(w.re + (1-w).rd(1-t)]. Setting NPV=0 and rearranging shows that using the pre-tax WACC of $wr_e/(1-t) + (1-w)r_d$ to determine pre tax cash flow (1+c) such that NPV = 0 gives equivalent result. (Note however, that this equality of approach is only correct for NPV=0 situations).

rates paid on deposits are less than wholesale market funding of the same tenor which involves minimal operating costs).

A second complication is that loan cash flows are rarely one-off, end of year, as used in this example. Default could happen at any time during the life of the loan, when repayments already made have affected the exposure at default, and the amount recovered might depend upon factors such as the state of the business cycle.[7] This makes the analysis more complicated, but similar in principle. Generally, banks will estimate a PD for a one year horizon (and combine that with conditional estimates of default in subsequent years), assume a LGD ratio (which may vary over time, and estimate the time path of EAD. Spreadsheet (or more sophisticated) modelling can be used to derive a zero NPV loan rate.

One important feature of the approach typically adopted by banks is that the assumed funding mix varies between loan products, while the cost of equity is assumed the same for all products. (The cost of the debt/deposit component will differ depending upon the timing of the cash flows involved in the loan – reflecting the term structure of interest rates – with this being conveyed to business units for use in pricing decisions via the internal *Funds Transfer Pricing* system). This is quite different from the approach advocated in corporate finance texts where a "pure play" approach to capital budgeting is advocated. In that approach, the same capital structure is assumed across all projects while the cost of equity should be assessed separately for each project based on its systematic risk (eg CAPM beta). And, of course, the capital structure of banks (very high leverage – treated deposits as debt) is quite different to that of corporates.

This different approach has been analysed by researchers such as Froot and Stein (JACF, 1998). They make the point that the value of a project with a given set of expected cash flows is normally assumed in corporate finance to be the same for any entity, since it is only the systematic (and not idiosyncratic) risk which is relevant for valuation. But for financial institutions, this is not generally assumed to be the case, because the size of equity capital component cost can vary between institutions as a result of their capital allocation policies. This means that the valuation can differ between institutions because of the interrelationship of the product risk with the existing capital structure of the institution. Their argument relates primarily to the fact that bank investment projects (loans) are illiquid with risks not able to be costlessly hedged via external transactions.

Another practical difference is that larger banks will operate an FTP system in which the business unit making a loan of, say, $100 will be allocated $100 of non-equity funding from the central treasury at

[7] The possibility that LGD (and also PD) might be more correlated with the business cycle for some loans rather than others, raises the issue of whether systematic risk is relevant to loan pricing and thus whether different costs of capital should be used to reflect this.

its specified transfer pricing interest rate for loans of that tenor and interest rate resetting characteristics. The bank will also apply a capital charge to the loan, reflecting (in principle) the equity capital notionally allocated to that loan multiplied by the difference between the required return on equity and the FTP rate. This mimics using the WACC as the cost of funding the loan as described above (as some simple algebra can demonstrate). Figure 5 illustrates this alternative (but equivalent) break down of loan pricing, and also includes a separate mark-up component reflecting perhaps market power of the bank in that loan market.

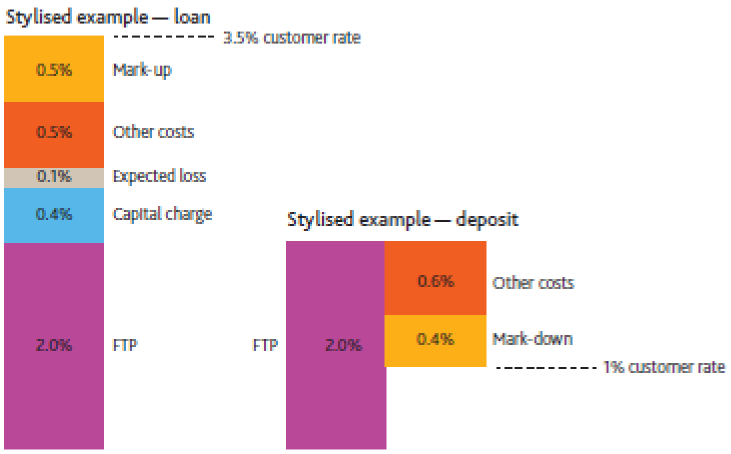

FIGURE 5 STYLISED EXAMPLE OF LOAN AND DEPOSIT PRICING (SOURCE BANK OF ENGLAND, 2015)

Figure 6 shows illustrates some of the reasons why the interest rate charged might differ for different loans. These include: different cost of funding (such as arising from different maturity); differences in credit risk; differences in operational costs; differences in the economic (or regulatory) capital required for that particular type of loan.

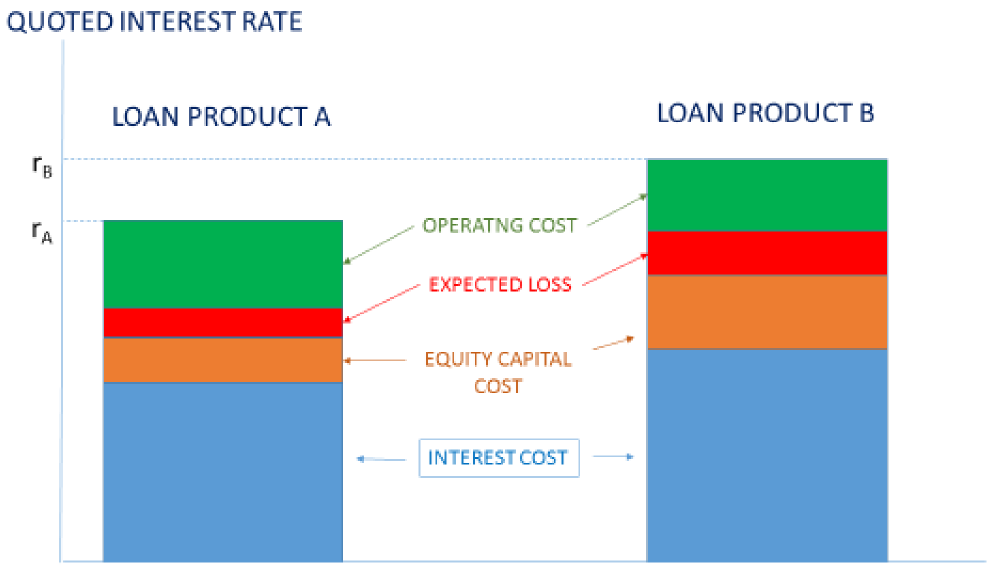

FIGURE 6: LOAN PRODUCT PRICING DETERMINANTS

Some simple relationships follow from this simple analysis. Rates charged on longer term loans should be higher, *cet par*, since the probability of the loan not having defaulted will decline with time. (The cost of funding longer term loans may also be higher). Loans with collateral provided will have lower LGD (and potentially lower PD given that loss of collateral associated with defaulting) so that the higher is collateral value relative to loan amount, the lower will be the interest rate. Interest rates charged on interest only loans should be higher than those on principal and interest loans since EAD will decline for the latter.

Pricing Off Balance Sheet Items

Suppose a Bank is considering providing a $100 principal amount (one year) guarantee for customer and will set a fee charged = $f per $1 of principal. It estimates that the risk associated with the guarantee requires $8 of economic capital.

The bank has a required return on capital of 16% and the expected loss per $1 of principal guaranteed d = 0.001 (or $0.10 for the $100 guarantee). The risk free interest rate is 5% p.a.

What fee should it charge for the guarantee? Hint: note that the guarantee involves no up front cash flows – hence the bank can invest the economic capital in risk free assets. The fee of f basis points will generate $ f.100 in fees, a return of r_f on the $8 of capital invested in the risk free asset, but a potential expected loss of d.100. This, as percentage of the $8 of equity needs to equal 0.16 and involves solving for f to achieve that outcome. In this case that generates a figure of f = 00.98 or 98 basis points as shown below.

Expected return on capital: f set to achieve re=0.16

=[f.100 + rf 8 - d.100] / 8 = [f.100 + 0.4 - 0.1]/8 = 0.16

100f + 0.3 = 1.28; f = 0.98/100 = 0.0098 i.e. 98 basis points

10.9 Assessing Performance of Loan Business Units

There are a range of alternative ways of thinking about loan pricing and the value added from a loan decision. One approach is to think of a Risk Adjusted Return on Capital (RAROC) hurdle rate as the return on equity capital allocated to the loan which needs to be achieved. Thus, one could adapt the WACC approach to convert it into a return on equity calculation such that:

Expected RAROC = [Promised revenues – operating costs – interest funding costs – expected loss]/Allocated Equity Capital

The loan would need to have an Expected RAROC above the required return on equity to add value.

A RAROC approach could be used as a measure of performance of a business unit such as one making loans. The actual RAROC (using *actual revenues* in place of *expected revenues minus expected loss*) could be calculated and compared with the required return on equity. While that could be done easily *ex post* for a single loan, application to a business unit's performance over (say) a year would be more complicated and need to recognise the multi-year nature of loans, and changes in provisions made etc. There is also a fundamental problem in using a rate of return measure of performance. A business unit might inappropriately turn down loan opportunities even if they promise a rate of return above the required rate, if they would reduce the average return on the loan portfolio. A simple rate of return performance measure does not take into account the volume of business on which that rate of return was achieved.

An alternative approach to assessing performance is to use a concept such as Economic Value Added (EVA). Expressed simply, EVA is calculated as:

EVA = (ROE – r).BV

where ROE is the accounting return on accounting value of equity, r is the required return on (the market value of) equity and BV is the book value amount of equity involved in the activity. This approach has its theoretical foundations in the Return on Investment (or Residual Income) valuation approach (which can be derived from a dividend discount (cash flow) valuation as shown in the Chapter 4 Appendix) which expresses current market value (MV_0) as:

$MV_0 = BV_0 + PV(\text{expected future abnormal earnings})$

where abnormal earnings in any future period T are given by (ROE_T – r).BV_{T-1} (and PV stands for present value). The difference between market and book value of equity is thus the present value of all future EVA's.

EVA could also be calculated as NOPAT – WACC*(Debt + BV(E)).

CBA uses a concept apparently similar to EVA described as Profit after Capital Charge (PACC) "as a key measure of risk adjusted profitability. It takes into account the profit achieved, the risk to capital that was taken to achieve it, and other adjustments". (2020 Half Year Results Presentation, p61)

10.10 Credit Risk Modelling[8]

There are ongoing developments in the field of credit risk modelling as researchers and lenders attempt to find better methods of distinguishing between higher and lower risk borrowers, and aligning interest rates charged with risk assessment. These developments relate to both assessment of individual loan risk as well as modelling of the risk of particular loan portfolios. Zamore et al (EMFT, 2018, working paper version) provide a survey of the vast academic literature on credit risk modelling.

Of course, models are no more than that, and can easily be flawed. So an important issue for banks is to ensure that their models are as accurate and reliable as possible. The internal structure of a model methodology could be flawed, the data used as inputs could be faulty, management may have a poor understanding of models bought from external vendors (or developed internally by others). Many large banks will try to deal with these issues by having a Chief Model Risk Officer (or Head of Model Risk) as discussed in this KPMG article on model risk management. One development has been increasing use of machine learning/algorithmic approaches/artificial intelligence/neural networks, drawing on increasingly large and detailed databases, for credit risk estimation which are discussed and compared in this S&P article. One important issue with reliance on such approaches is the issue of human understanding of the workings of complex algorithms, and responsibility for the decisions which result from their use.

Credit risk arises primarily from lending activities, but trading book activities, investments, inter-bank transaction, guarantees are also important

For assessing credit exposure, most banks will calculate expected Loss (EL) as:

EL = PD x LGD x EAD

[8] There are a range of documents on credit risk modelling and management from the Basel Committee such as these 2006 2010, 2010, 2015 documents and this 2015 one from the Joint Forum.

where: PD is probability of default over a specified horizon (1 year or lifetime of credit facility); LGD is loss given default taking into account likely amount and timing (and thus discounting) of recoveries, and may be calculated under the assumption of an economic downturn; and EAD is exposure at default. For most exposures a 1 year horizon for EL will be used, but lifetime EL will be used for those which are already impaired (eg repayments 90+ days overdue) or some sub-investment grade exposures.

For banks using the IRB approach for credit risk, a regulatory expected loss figure is calculated using the banks' estimates of PD, LGD and EAD, (on a *through the cycle (TtC)* rather than *point in* time (PiT) basis)[9] and these figures are inserted into regulatory formula to calculate Risk Weighted Assets due to credit risk. A TtC estimate will not take into account current macroeconomic conditions, whereas a PiT estimate will.

Figures on these various parameters, including the extent to which actual losses (and PDs and EADs) differ from those expected can be found in the Pillar 3 Capital and Risk disclosures of the banks.

As earlier discussion suggests, there are three main elements of credit risk modelling: estimation of PD; estimation of LGD, and estimation of EAD. The objective is to use information derived from samples of past borrowers to identify important determinants of PD, LGD and EAD, and use these to predict likely values of these variables for future borrowers.

Arguably, modelling of LGD has proven the least robust. Recoveries can take significant periods of time after a default occurs, can depend on the relationship between borrower and lender, efforts expended in attempting recovery etc.[10] Moreover, since most cases involve either full recovery or zero recovery, but with others in between, drawing reliable statistical inferences from such distributions can be difficult.

But there are also complications for statistical modelling of PD since for most loan classes, the probability of default is very low. Drawing on past data to identify relevant characteristics which determine PD leads to an unbalanced sample in which most observations do not default, creating concerns about the precision of estimates from the statistical models applied.

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[9] NAB's 2017 Pillar 3 report (p29) defines these as "PiT, which estimates the likelihood of default in the next 12 months taking account of the current economic conditions. PiT PDs are used for management of the portfolio and the collective provision calculation. TtC, which estimates the likelihood of default through a full credit cycle. TtC PDs are used for regulatory and economic capital calculation".

[10] There is also an interesting issue of what discount rate should be used in converting a future LGD into its present value equivalent.

EAD modelling can also be quite complex, since it depends upon the repayment pattern of the borrower, or the drawdown rate in the case of loan commitments. As in the case of the other parameters, there is a question of what time horizon to use – with an annual horizon being relatively common.

Most emphasis has been on PD modelling and there are a variety of approaches, generally broken down into two categories.[11] *Structural models* attempt to estimate PD from an economic (structural) model of the borrower – and the Merton model (discussed below) and subsequent variants thereon is the most well known. (A specific structural model underpins the Basel approach to determination of required capital). The alternative approach is referred to as the *reduced form* approach in which the PD is expressed as some function of variables thought relevant to the default event happening. The Altman Z-Score and Ohlson H-Score are early examples of this approach. From a sample of (in these cases) companies, a discrete dependent variable (default/non default within some time period) regression (such as a Logit or Probit) is run using relevant company characteristics as explanators. The resulting coefficients then provide weights to apply to those same characteristics for other companies (or out of sample) to predict the likelihood of their default. An alternative approach is to use some form of *hazard model* in which the dependent variable is the likelihood of the company failing before various dates.[12]

Another possibility is to draw estimates of PD from the transition matrices available from the major Credit Rating Agencies (Moodys, S&P, Fitch). These matrices show the probability, based on past experience, that a firm currently with a rating of, for example, A will be in a different (or the same) ratings grade (eg AA, AA-, A+, A, A-, BBB+, etc) in a year's time. Because the matrices also include a grade corresponding to default, an estimate of the one-year PD can be derived for any firm once its rating is known.

Of course, many firms are not rated by the agencies, but larger banks will have developed a "mapping" of their own internal ratings into those of the agencies, such that the transition probabilities can be applied to unrated firms. (The CBA mapping of their internal ratings into those of S&P and Moody's can be found here (p27)). One complication is that the transition matrices are based on companies which have publicly issued (and rated) debt, and there may be fundamental differences between those types of companies and those which rely on bank loans. And, while the historical transition

[11] http://www.bis.org/publ/bcbs49.pdf gives a now somewhat dated, but still useful, overview of the issues. See also this Bank of England 2015 article.

[12] Campbell et al (JF, 2008) provide an overview of a number of reduced form approaches.

matrix probabilities perform quite well as predictors of future ratings changes at an overall level, there have been many notable examples of failures of companies with high ratings up until that point.

Another issue for bank use of ratings agency information is that this PD information is an average of "through the cycle" experience, not dependent on the current "point in time" which is of more relevance to a bank considering a loan.

Of course, one problem with any of these approaches is that the process of a borrower company defaulting is not an event independent of the bank's activities. It may respond to a borrower in difficulty by changing loan repayment terms which affects the likelihood of default. Most studies have tended to focus on default events for companies with bonds on issue where this may be less of a problem. A further problem is that actual default is only one feature of default risk. A bank may find the mark to market value of its exposures to borrowers affected by changes in the credit rating of the borrowers.

The Merton Model

In 1974, Merton developed the very influential structural model for assessing corporate credit risk based on option pricing. It involves a stylised model of the borrower and the obligation. While empirical tests of the model have implied problems of calibration[13], this has led to adjustments to such simple models and development of more complex variants. One example, among a number of vendor credit risk models, is Moody's KMV model. The Basel Committee's Internal Ratings Based approach to capital requirements is based on credit risk modelling for loan portfolios derived from Merton's original approach (and discussed in Chapter17).

Merton assumes the firm has one discount bond on issue maturing at T with face value F. V is the value of the firm's assets which follows a standard GBM process assumed in many option pricing models. Equity (E) is a call option on the firm's assets, and μ is the asset value growth rate. Using standard option pricing theory, the value of equity is given by the usual Black Scholes formula where the underlying is the firm asset value (V) and the strike price is the debt face value (F). The volatility of the asset value of the firm (σ_V) is related to the volatility of its equity via the leverage factor.

$$E = V\mathcal{N}(d_1) - e^{-rT}F\mathcal{N}(d_2),$$

$$d_1 = \frac{\ln(V/F) + (r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}$$

[13] See, for example, Bharath and Shumway (RFS, 2008).

$$d_2 = d_1 - \sigma_V \sqrt{T}$$

$$\sigma_E = \left(\frac{V}{E}\right) \frac{\partial E}{\partial V} \sigma_V$$

$$\sigma_E = \left(\frac{V}{E}\right) \mathcal{N}(d_1) \sigma_V$$

In these formulae, r is the risk free rate and $\mathcal{N}(.)$ stands for the cumulative normal distribution value of the argument in the brackets. The *risk neutral* probability of default (the probability, under an assumption of a risk neutral world, that the equity value will be less than the debt obligation at time T) is given by the $\mathcal{N}(d_2)$ value. The implied actual probability of default (PD) can be estimated by substituting an assumed asset value growth rate for the risk free rate in the formula for d_2, and the argument of that function (as popularised by the consulting firm KMV) has become known as the distance to default (DD)

$$\pi_{\mathrm{KMV}} = \mathcal{N}\left(-\left(\frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}\right)\right) = \mathcal{N}(-DD)$$

$$DD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}$$

There is a plethora of proprietary credit risk models aimed at calculating either probability of default or value at risk (or other risk measures) due to credit exposures both for individual assets and for loan portfolios. For portfolios, the models need to incorporate an allowance for correlations between the values of assets in the portfolio. These include: CreditMetrics; CreditRisk++; MercerOliverWyman model; McKinsey's Credit Portfolio view.

CreditMetrics

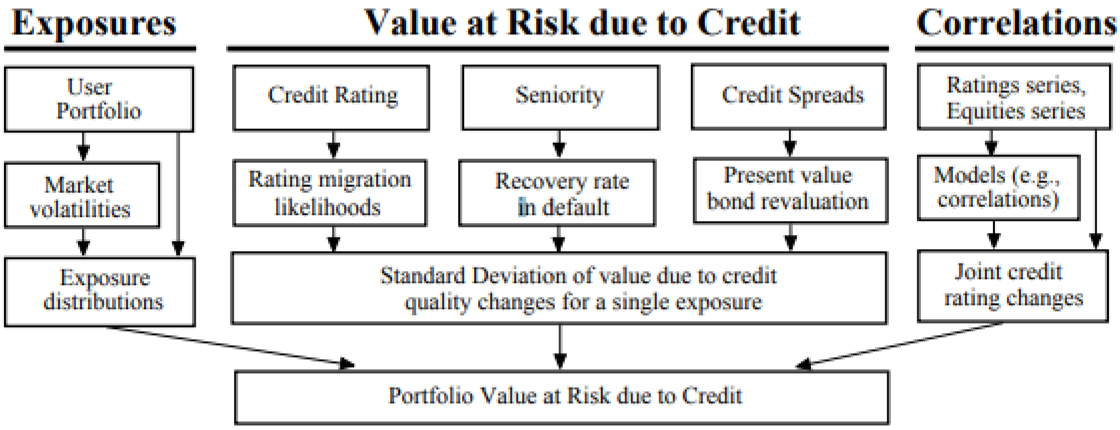

FIGURE 7:CREDIT METRICS OVERVIEW: SOURCE - MSCI

CreditMetrics enables a VAR approach. For example: Given a transition matrix of risk grades of loans/bonds (ie prob of going from one grade to another in 1 year)

- If grade = default, recovery reflects seniority
- If grades = solvent, use forecast market prices based on yield curve for that grade

One can estimate distribution of MTM returns based on changes in prices associated with transitions (but accounting issues!). For a portfolio, there is a need to consider transition correlations of individual assets, but with 2 assets and 10 risk grades, we have 100 possible combinations – and this grows exponentially with more assets. Hence, use some model to simplify correlation structure, and can derive expected loss on portfolio and VAR.

10.11 Credit Risk Mitigation

Lenders take actions both *ex ante* and *ex post* to reduce the risk of borrower default and loss given default. Banks will limit the amount of credit risk via limits on exposures to various counterparties or by geographical or industry segments. Banks will also seek appropriate collateral as security. Where many transactions occur with the same counterparties, *master netting agreements* (which operate when one party defaults) will be put in place. For derivative transactions, it is common to have a *credit support annex* (which specifies collateral arrangements) as part of the usual documentation.

Collateral

One of the obvious actions is through the requirement of collateral, generally of at least the value of the loan provided, which should reduce both the PD and LGD. Of course, one of the issues arising is whether the borrower has clear title to the collateral provided, such that the lender can claim it should default occur.

Lending against real estate will typically be way of mortgage, giving the lender a first claim on the property should the borrower default. Property transfers involving such borrowing have historically involved a complicated paper based settlement process whereby transfer of funds between purchaser and vendor (involving bank cheques) occurs at the same time title is transferred to the purchaser and the lender's mortgage claim over the property established. Modern technology is enabling this to be done electronically, with PEXA providing the platform in Australia.

A major risk in property development lending is that while a loan may be secured against the property development, failure of the building firm involved before completion may mean the collateral value is significantly below the loan outstanding. Half-finished buildings or a hole in the ground may have little resale value.

In the case of personal property offered as collateral, a number of countries have established registers which show current ownership and outstanding claims on such properties. This protects:

- potential purchasers of goods such as motor vehicles (provided that they check) from purchasing an asset which might be repossessed by a lender with a claim against that asset;
- potential lenders from making loans where there is a superior claim in existence; and
- existing lenders - to the extent that it reduces the extent of owner-borrowers being able to dispose of assets without meeting repayment obligations.

In Australia, the Personal Properties Security Register (PPSR) performs such a role, and unless a claim is registered, the lender becomes an unsecured creditor.

Collateral can also take the form of financial securities, such as government bonds or shares. Repurchase agreements are short term loans provided against collateral such as government bonds or other debt/hybrid securities. Margin lending involves the securities purchased by an individual using the loan being available as collateral to the lender.

Covenants

Many lenders will impose covenants on borrowers requiring them to meet certain conditions (as well as loan repayments) to avoid being declared in default. There are both "negative" and "positive" covenants. Positive covenants are that the borrower will do something. The negative covenants involve requirements that the borrower ensures that certain things do not happen. For a business borrower this may involve: limits on leverage; ensuring no senior (or equal ranking) claims are issued; having a minimum interest coverage ratio.

Covenants are one way in which a lender can monitor a borrower after the loan has been granted. The objective of such monitoring is to ensure that the borrower does not take actions which increase the possible loss on the loan. Prilmeieir (JFE, 2017) provides an analysis of how covenants are structured to generate information for the lender as a monitor, and how these evolve over time with the relationship between lender and borrower.

Delegated Monitors

Diamond (RES, 1984) – a simpler version available here - argues that one reason for the existence of banks (and for their making loans financed by short term deposits) is a role as "delegated monitors". Most loans involve larger amounts than depositors could individually finance, and a collection of depositors doing so leads to a "free-rider" problem regarding monitoring of the borrower. (This is independent of whether such individuals have sufficient expertise at either *ex ante* credit assessment or *ex post* monitoring skills). The bank lender undertakes the monitoring role on behalf of depositors (as indirect lenders). By issuing short term deposits, Diamond argues that the bank can credibly signal to borrowers that it will undertake such monitoring.

On-demand loans and non-monetary defaults

Many bank loan contracts will have conditions which allow for the bank to demand repayment of the loan at any time ahead of the specified repayment schedule, even if the borrower is meeting repayment obligations and other loan conditions. This enables a bank which is suffering a liquidity crisis to call in outstanding loans to meet deposit outflows. Doing so, of course, may lead to significant defaults (and reputational effects) and convert a liquidity problem into a solvency problem.

More generally, such a provision allows the bank to take action which might reduce potential losses on a loan (even though the borrower is meeting current commitments). For example, the loan may be secured against a commercial property from which the borrower obtains rental income. In a depressed economy, an expected further decline in commercial property prices and in economic activity may lead the bank to believe that calling in the loan, even if it leads to default, will involve lower losses than allowing the loan to continue (with a high probability of a future default when the collateral value will have fallen further).

In Australia, there were numerous cases of such "non-monetary default" actions following the financial crisis, particularly involving BankWest. (See Senate Inquiry). This issue was highlighted by the FSI Final Report in 2014, and the subsequent Carnell Report in 2016 recommended that such conditions not be permitted in loan terms for small businesses. The Royal Commission also made recommendations in this regard and the Australian Bankers' (2019) revised "Banking Code of Practice" contains limits on such conditions.

Netting (Compensating Balances)

In the USA a common requirement of loans was that the borrower maintain some amount on deposit with the lender (compensating balances). While this, in principle, reduces the loss given default, it also serves to increase the effective interest rate on the loan if the deposit interest rate is below the loan interest rate.

In transactions between financial institutions, there will often be situations in which the two parties have exposures to each other. Netting conditions provide for amounts owed by a bank to a defaulting counterparty to no longer to be owed (if they are less than the amount defaulted on).

Risk Transfer

A bank may originate a loan but transfer some part of the default risk (for a fee) to some other party.

Securitisation

Securitisation (see Chapter 11) is an example at the loan portfolio level, where a package of loans originated by the bank is sold to investors with the bank retaining only some (or none) of the risk. Securitisation is also used by banks as a funding mechanism. The credit risk capital requirements for the loans involved in a securitisation depend on the extent to which the credit risk is transferred to a third party without recourse to the bank and are given in *APS 120 Securitisation*.

Credit Derivatives

Credit default swaps (CDS, see Chapter 12) are one example of credit derivatives. It is only in the case of large borrowers that a CDS is likely to be available on a particular borrower enabling hedging of a loan to that borrower (and the terms of the CDS can mean that there is still some residual risk involved, such as when the scale of the CDS or its maturity do not match those of the underlying loan). The existence of CDS Indexes such as the iTraxx enable Australian banks to adjust their overall credit risk position via transactions in that market – although the specific characteristics of the iTraxx (it is based on credit grade ratings for 25 entities) mean that there will always be a significant basis risk relative to the bank's own loan portfolio. Banks may also negotiate a loan portfolio credit swap with another bank whereby the bank passes the credit risk of a particular loan portfolio (such as a parcel of its agricultural loans) to another bank in return for accepting the credit risk of a parcel of different loans (such as SME loans) of the other bank. In this example, the bank would be able to reduce its credit exposure to the agricultural sector by taking on credit exposure of SMEs. Needless to say, the resulting exposure to the counterparty bank's loan approval and management processes needs to be considered in striking a deal.

Lenders Mortgage Insurance (LMI)

In the case of housing loans, banks will offer require a borrower to pay for Lenders Mortgage Insurance. This typically occurs for high loan to valuation (LVR) loans (80 per cent or above). It involves a specialised insurance company (eg Helia[14] in Australia) agreeing that in the event of the borrower defaulting, it will pay the lender the resulting shortfall (after sale of the property involved). While the borrower makes the insurance payment, it is the lender who gets the benefit of the insurance. Helia has the largest share of the LMI market and counts CBA, BoQ, and ING among its customers. Also active in the Australian LMI market is QBE which in 2022 counted NAB and Bank Australia among its customers. Some large banks such as ANZ and Macquarie self-insure with LMI being offered through a subsidiary generally referred to as a "captive insurer", while Westpac sold its LMI business to ARCH Capital Group in 2021.

Intending borrowers with high LVRs (above 80 per cent) can obtain estimates of the likely cost of mortgage insurance to them using calculators such as found here. At the end of January 2023, a person borrowing $850,000 under a 30 year mortgage for purchase of a $1 million house would have been charged a one-off premium of $11,135. If the LVR was 90 per cent the premium was $22,392. (The premium may vary depending on the borrower circumstances and lender involved). One issue here is whether the borrower receives an refund of the premium paid if they pay out the mortgage sooner – such as if the house is sold to purchase another house. (And because of such events, the average actual life of a mortgage loan is around 5 or so years, rather than the 30 year contractual life). This will depend on the terms of the LMI policy agreed between the bank and the mortgage insurance company (and the Banking Code of Practice requires the lender to provide information about this when a loan is negotiated). It is not clear how many borrowers are eligible for (and claim) such a refund if they sell the property, not how many are fully aware of this issue.

Aggregate data on the LMI sector can be found in APRA's Quarterly General Insurance Performance Statistics. The average premium paid in 2022 was around $8,000, with total premiums paid of around $1 billion in that year. The loss ratio (the proportion of policies on which a payout was required was around 20 per cent).

10.12 Loan Terms and Credit Rationing

A fundamental problem for lenders is imperfect information which is relevant from both an *ex ante* and an *ex post* perspective. *Ex ante*, there is the problem of assessing the risk characteristics of the borrower. As well as needing to assess the expected loss (EL) in order to determine the appropriate

[14] Helia was known as Genworth until a name change in late 2022, which reflected the end of majority ownership by the US based Genworth Financial. It entered the Australian market in 1997 by taking over the Government owned Housing Loans Insurance Corporation which had been established in 1965.

size, repayment arrangements, and price of a loan, it is also necessary to identify how the risk characteristics of the loan would contribute to the overall risk of the loan portfolio. *Ex post,* there is the problem of monitoring the loan, ensuring the borrower has appropriate incentives for repayment, and management of the loan arrangements when the borrower is in financial distress or default. These issues give rise to *Adverse Selection* and *Moral Hazard* as two key considerations.

One common characteristic of loan markets is *credit rationing*, where lenders are not willing to provide borrowers with a loan of the size demanded – even if borrowers are willing to pay a higher interest rate. This could result from interest rate ceilings due to regulation, but is also a feature of unregulated markets.

Credit Rationing has, at various times and in various countries, been attributed to the existence of regulatory imposition of maximum ("ceiling") loan interest rates. This has often been done to "protect borrowers". For example, in Australia there is currently a maximum interest rate prescribed for Small Amount Credit Contracts (such as payday loans).

A simple one-period example can illustrate why. If L is the amount to be lent at a contractual interest rate of r, the promised repayment is L(1+r) = LR. But if the probability of default (p) increases with promised repayment (ie p = p(LR)), the expected profit to the lender is E(π) = (1-p(LR)).(LR) + p(LR).X – (1+c)L where X<LR is the amount recovered in default and c is the cost of funds. (Let C=1+c, for notational convenience). Assume for simplicity that the probability of default increases linearly with repayment obligation, ie p=LR (for 0<LR<1, such that LR =1 is maximum repayment allowable) and X = 0 (zero recovery if default occurs). Then E(π) = (1-LR)(LR) – CL,

Assuming a risk neutral lender (who only cares about expected profit), maximizing with respect to L for given R gives the optimal loan size $\hat{L}$:

$$\frac{\partial E(\pi)}{\partial L} = R - 2LR^2 - C = 0$$

$$\hat{L} = \frac{R - C}{2R^2} = \frac{1}{2R} - \frac{C}{2R^2}$$

Then differentiate with respect to R to see how $\hat{L}$ changes with R, to get

$$\frac{\partial \hat{L}}{\partial R} = -\frac{1}{2R^2} + \frac{C}{4R^3}$$

such that:

$$\frac{\partial \hat{L}}{\partial R} > (<) 0 \; as \; C > (<) 2R$$

Figure 8 shows the resulting relationship between loan size and contractual interest rate, which is backward bending. This specific case reflects the very simplifying assumptions made (including risk neutrality) but generally, as long as expected loss (EL) increases (relative to loan size) with repayment obligation a result such as shown below will occur. Higher contractual rates, after some loan size is reached increase the probability of default sufficiently that the expected return on the loan declines unless the loan size is reduced to offset that effect.

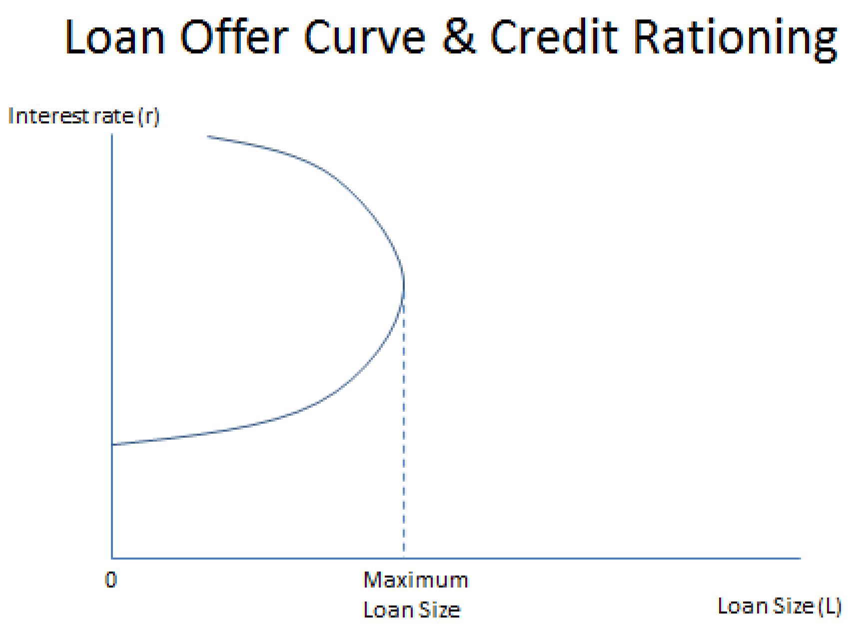

FIGURE 8: LOAN OFFER CURVE

Credit rationing due to adverse selection and moral hazard. The simple loan offer curve model derived above focuses on one borrower and assumes that the lender has information about default risk of that borrower. In practice, information is imperfect and a problem for lenders is to separate borrowers into different risk classes and price loans appropriately. There have been a number of papers which have used information asymmetry to show that credit rationing may emerge as a feature of loan contracts aimed at reducing problems arising from adverse selection and moral hazard. Stiglitz and Weiss (AER, 1981) is the most well-known one, but there is a long literature, including a recent contribution by Ambrose et al (JF, 2016) examining similar issues arising in the sub-prime mortgage market in the USA prior to the GFC.

Stiglitz and Weiss argue that for a bank dealing with a range of different, but indistinguishable borrowers, as the interest rate increases the composition of borrowers changes towards more risky borrowers. This is an *adverse selection* effect. To illustrate, assume two borrower types A and B with projects where expected returns are equal, $P^aX^a = P^bX^b$, but where $X^a < X^b$ is return if successful (with probabilities $P^a > P^b$) or 0 otherwise, such that A is the safer borrower. The loan size is \$1 at interest rate of r (so promised repayment is 1+r, and investment required is 1+e such that risk neutral borrowers will require net return on their equity e of $e(1+r_e)$.

Borrower i's expected net return is $P^i(X^i - (1+r)) = P^iX^i - P^i(1+r)$ and will thus apply for a loan if: $P^iX^i - P^i(1+r) > e(1+r_e)$.

As shown in Figure 9, at r=0, $P^AX^A-P^A < P^BX^B-P^B$, but as r increases, it has less effect on the net return for the risky borrower B (because $P^B < P^A$ and $P^aX^a = P^bX^b$) so there will be some value r* at which net return for A falls below required return but remains above it for B. The lender then has a change in composition of borrower applicants to the more risky group. The expected return to the bank from its loan portfolio will thus drop at r* (assuming it makes loans of \$1 to all applicants).

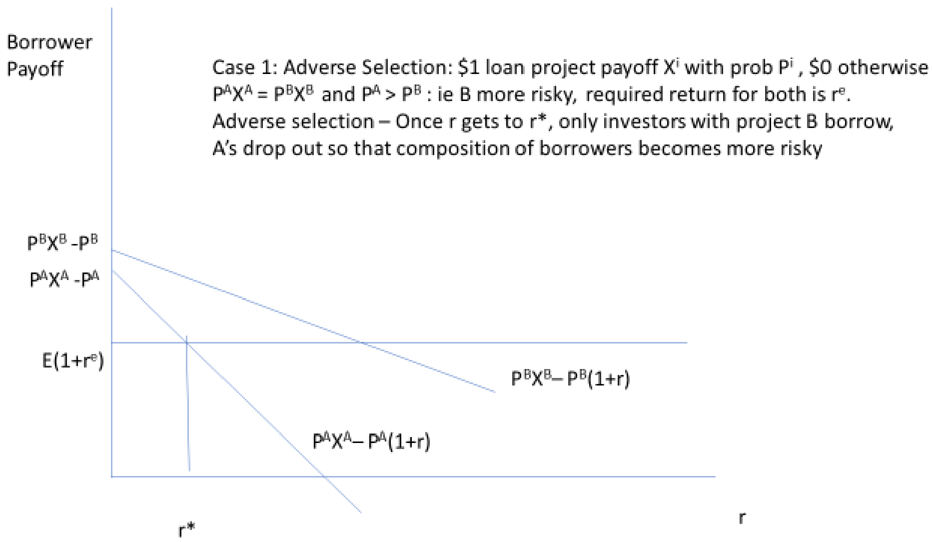

FIGURE 9 ADVERSE SELECTION EFFECT

Moral Hazard

The moral hazard effect of charging a higher interest rate can be seen by assuming that Figure 10 applies and refers to one borrower who has a choice between the two projects A and B. (It is no longer assumed that $P^aX^a = P^bX^b$, and instead that $P^AX^A\text{-}P^A > P^BX^B\text{-}P^B$. It is apparent that as the interest rate increases, the borrower has an incentive to shift to the more risky project B. Because the lender's return for project i is P^i (1+r) where P^i is probability of a successful project, it is clear that if the borrower shifts from project A to B (where $P^B < P^A$) the lender is worse off. (In this simple example, the lender gets zero if the project fails).

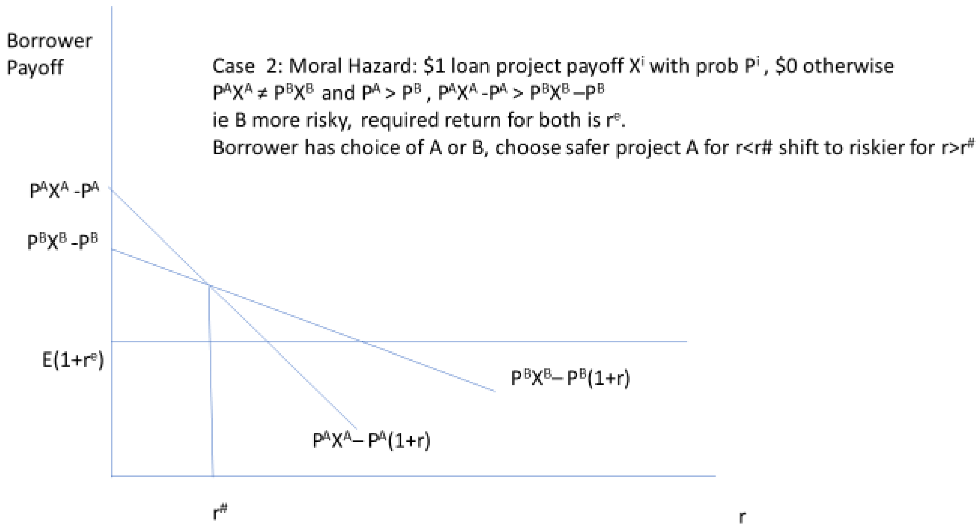

FIGURE 10: CREDIT RATIONING - MORAL HAZARD EFFECT

Both the adverse selection and moral hazard effects illustrate that banks may not benefit from charging higher interest rates, and lead to the important question of whether banks are able to set loan contract terms which cause borrowers to self-select into different contracts – each of which is optimal from the bank's perspective for that type of borrower. (Of course, banks will use other information to try and identify borrower types as well). As a simple example, consider a case where there are honest borrowers who will repay if able to, and dishonest borrowers with no intention of repaying. *Ex ante* the bank cannot identify which are honest and which dishonest. Suppose the bank offers two loan contracts where one is for a large amount at a high interest rate, and the other is a smaller amount at a lower interest rate. If borrowers are unaware of the signalling implied by their choice, dishonest borrowers will opt for the larger loan (with higher interest rate) since they have no intention of repaying. The bank would reject such borrowers. This would be a (trivial) example of a *separating equilibrium* in which different individuals get offered different loan terms reflecting their implied repayment characteristics. In a *pooling equilibrium*, all borrowers get offered the same loan terms, because it is not possible to design terms to achieve a self-selection outcome. Which outcome prevails will depend *inter alia* on the distribution of characteristics of the borrower population as well as the nature of competition between lenders.

Needless to say, the Rothschild-Stiglitz perspective has not gone unchallenged. In a number of articles, De Meza and Webb demonstrate that by changing some model assumptions an outcome of asymmetric information can be “over-lending” to poor quality firms rather than credit rationing of good quality firms. (See Bonnet et al (AE 2016) for an overview of this literature).

McCarthy et al (AJM 2017) examine credit rationing of Australian SMEs using a large-scale survey in 2010 and 2011. They find credit is more likely to be rationed for firms which are smaller, non-export-oriented, non-agricultural, not product-innovative, and with female CEOs. They also find mismatches of what firms and banks see as important in applying for and assessing loan applications.